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AN APPROACH FOR THE CONTROL ERROR CALCULATION UNDER FUZZINESS

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ABSTRACT

The present paper recommends options to represent setpoints and actual values in automation tasks using fuzzy theory. It discusses problems arising in the calculation of control errors in detail and presents preliminary results on the development of two novel approaches. Finally the method will be applied in a simulation based case study to control the relative air humidity of a room with a predictive control strategy.

Index Terms - fuzzy decision making, predictive control strategies, multistage fuzzy control, control error calculation under fuzziness

1. INTRODUCTION

In some automation tasks the values of setpoints and controlled variables are uncertain, imprecise charged with noise and may even be faulted. The final demanded values are not defined by means of fixed setpoints. They are rather based on tolerance values (ranges), thresholds, classified limits or multi valued states. Particularly, in the area of air conditioning and climate management, only rough values of setpoints are available: mainly because climatic requirements are often described linguistically and provided with lack of knowledge. These characteristics suggest applying the fuzzy theory, using fuzzy numbers and intervals to formulate setpoints and to judge controlled variables [1].

Climate goals are described by classifying zones, which can be attributed to the linguistic terms, for example *inappropriate*, *acceptable* and *ideal*. So a transforming from the crisp to the fuzzy world can be done by membership functions (figure 1).

Furthermore, the acquisition of process variables is rather uncertain. At a first level errors are caused by the inaccuracy of sensors. More different error sources are such as model inexactness (differences) or stochastic influences. Hence measured, observed and predicted process variables are always vague in reality. This uncertainness can also be described by using fuzzy numbers and fuzzy intervals.

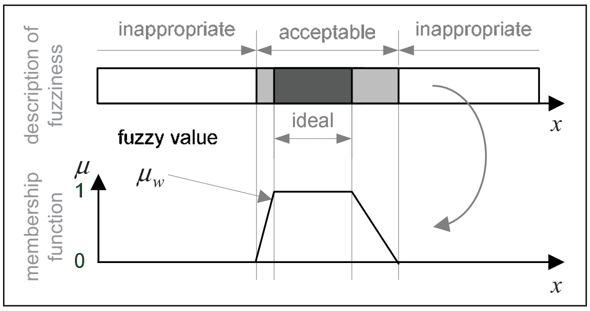

Figure 1: Formulation of a setpoint under fuzziness

The fuzzy theory doesn't make use of probability values; its focus lies on the possibility. If a fuzzy representation is used for actual values, the membership degree for each value represents the degree of possibility for each real world value. It is necessary to define a method for the formulation and calculation of the fuzziness of actual values. In mathematics of data analyzing usually statistical methods are used to get probability qualities, but they are also suitable to extract possibility qualities. The difference and the assignment of probability and possibility are discussed elsewhere like [2], [3], [4]. Without deeper and widespread explanations, the (normalized) probability density may be defined as a lower limit for the possibility degree (figure 2). An equation for the relation between measured, observed and predicted actual values to the degree of the possibility distribution has to be defined:

$$\mu_x = f(x_M) \tag{1}$$

The membership function does not have to be consequently the same for every measured value, but, if it is, however, it is possible to use fuzzy modifiers or parameter adaption to create the relation between the measured value and the fuzzy actual value.

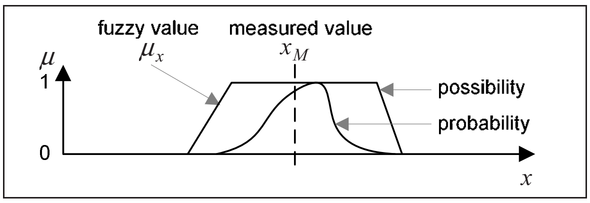

Figure 2: Formulation of an actual value under fuzziness; difference: possibility and probability

2. CALCULATION OF THE CONTROL ERROR

Typical tasks of automation – starting with conventional controls, diagnostics and observation up to prediction – are based on the control error calculation, which is a comparison of desired and actual values. This poses the question how aspects of vagueness and fuzziness can be taken into account; this problem is discussed in a few papers, like [5].

2.1. Conventional method

In most control strategies the calculation of the actuator signals is based on a comparison of setpoints and actual values of the controlled variables. Generally a function can be defined, which gives a criterion for the state of the process:

$$J = f\left(x_M, w\right) \tag{2}$$

Using conventional process values, the control error is calculated as the difference between setpoints and actual values or as functions of this difference, like the absolute value or the square of it. This criterion is also used in optimization tasks (like control parameter adaption), were the value of J has to be minimized.

2.2. Known method by fuzzy setpoints

Usually it is very easy to find a criterion if the setpoint is fuzzy: every actual value is a unique value in form of a degree of the ideal value; the illustration is shown in figure 3. The value of the resulting function ranges between 0 and 1, equal to the membership function of the setpoint. Defining the objective function as a fuzzy goal μ_J leads to:

$$\mu_J\left(x_M\right) = J\left(\mu_w, x_M\right) = \mu_w\left(x_M\right) \tag{3}$$

The following features are resulting:

- nonlinear effects in the rating will be considered;
- it is possible to define forbidden areas in the universe of discourse, while setting the membership degree to 0;
- it is possible to define a (weighted) compromise in a multi criteria decision making using the t-norm of all single criteria;
- the rating function is already scaled between 0 and 1, thus obviously weightings between various process values can be defined and
- fuzzy modifiers (overview in [6]) can be used to consider linguistic hedges.

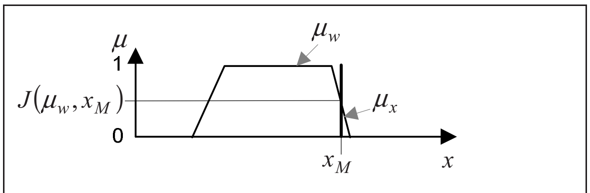

Figure 3: Fuzzy setpoint as a fuzzy goal

The second application case will demonstrate a scenario where also the actual value includes fuzziness, too. The approach above proposed cannot be used. By defining new methods it would be an approach to satisfy the above listed features as well. An initially obvious possible solution to develop a new criterion would be to use the difference between the centers of gravity. [7] shows, that this approach is not very efficient, because the rating is linearized and the information about the fuzziness is completely lost.

2.3. Alternative approaches

Two suggestions are established in the following subsections, which are based on the linguistic interpretation of the demand between possible actual values and undesired setpoints. To present the features of fuzzy goals, a relation between the μ_J based on μ_w and x_M has to be defined.

2.3.1. Optimistic approach

To deduce the shape of the combination from both fuzzy values (setpoint and actual value), a mathematical aggregation operation will be a suitable way to simulate the human's interpretation of the linguistic decision making. One suggestion is the maximization of the intersection from possible actual values and desired setpoints (figure 4). A linguistic description could be: "*The more possible actual values in the vicinity of desired setpoints, the higher is the rating of the process state!*"

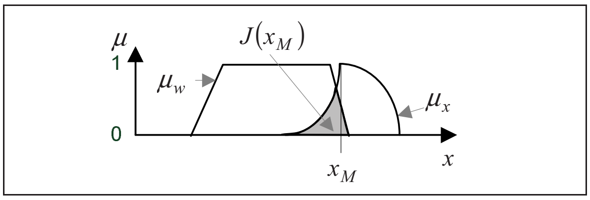

Figure 4: Intersection of desired setpoints and possible actual values as quality criterion

The intersection of both fuzzy values may be realized by creating the t-norm of them. The size of the intersection area (the integral) gives a quality criterion for the objective function. Form a theoretical standpoint every known t-norm could be used for this propose. As an example the algebraic product is used in this paper:

$$\begin{aligned} J\left(x_M\right) &= \int T\left\{\mu_W, \mu_M\left(x_M\right)\right\} \cdot dx \\ &\cong \sum_x \mu_W \cdot \mu_M\left(x_M\right) \end{aligned} \tag{4}$$

2.3.2. Pessimistic approach

Another suggestion can be to maximize the union from possible actual values and undesired setpoints (figure 5). A linguistic description could be: "*The less possible actual values occur in the vicinity of undesired setpoints, the higher is the rating of the process state!*"

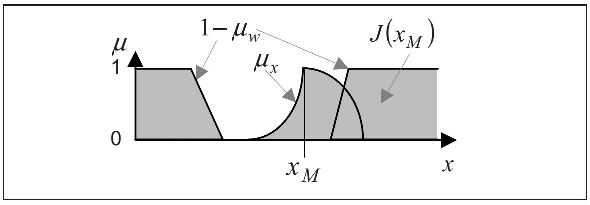

Figure 5: Union of undesired setpoints and possible actual values as quality criterion

At first the complement of the setpoint has to be created. To derive a quality value the union of both fuzzy sets is calculated applying an s-norm. Making use of De-Morgan's Rule, it is also possible to operate with t-norms. Using the algebraic product as the t-norm leads to:

$$\begin{aligned} J(x_M) &= \int S\{1-\mu_W, \mu_M(x_M)\} \cdot dx \\ &= \int 1 - T\{\mu_W, 1-\mu_M(x_M)\} \cdot dx \\ &\cong \sum_x 1 - \mu_W \cdot (1-\mu_M(x_M)) \end{aligned} \tag{5}$$

2.3.3. Creating a new fuzzy goal

Both suggestions noted above are able to consider the fuzziness in setpoints and in actual values. If all individual fuzzy values of the actual value are established, the relation of the objective J and the actual value x_M has to be created. To retain the features of chapter 2.2., it is necessary to scale the objective function between 0 and 1 – finally a new membership function results, which is the new created fuzzy goal:

$$\mu_J(x_M) = \frac{J(x_M) - \min\{J(x_M)\}}{\max\{J(x_M) - \min\{J(x_M)\}\}} \tag{6}$$

2.3.4. Comparison of both approaches

At a first look both suggestions seem to be similar: the linguistic interpretation and the mathematical formulation do not imply a very severe effect. Figure 6 shows two scenarios (left and right) with the same setpoint but different actual values. The fuzziness of the actual value has always the same distribution around the measured value; the shifting of the function is in relation of the measured value. Obviously the two methods have different effects to the modification of the fuzzy goal.

The difference between the two methods can be explained as follows: by means of the optimistic approach actual values with low possibilities will already be classified as plausible and thus high weightings. The consequence is a generally higher rating, especially for values in the vicinity of the ideal zone of the setpoints. The pessimistic approach produces a controversial effect: possibility degrees of actual values get critical attention.

Actual values with a low possibility degree get only a high weighting, if the degree of the desired setpoint is high, too. The area of ideal ratings in the fuzzy goal is more concrete as in the setpoint and. Independent of the used method, a fuzzy operation for aggregation of fuzzy setpoints and actual values can be defined as follows:

$$\mu_J(x_M) = G\{\mu_w, \mu_x(x_M)\} \tag{7}$$

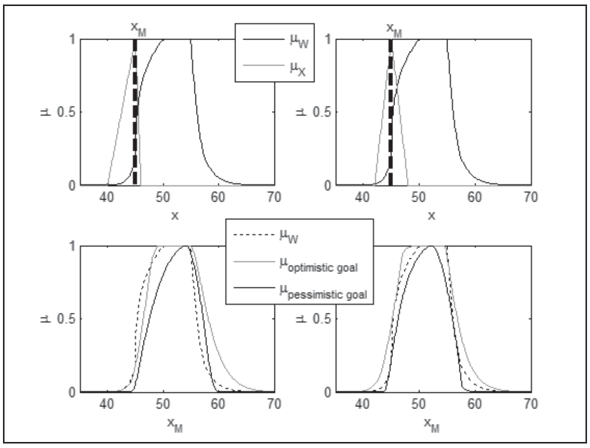

Figure 6: Left side: example 1; right side: example 2; above: setpoint and actual value as fuzzy intervals; below: new optimistic and pessimistic fuzzy goals

3. APPLYING THE FUZZY RATING IN MODEL PREDICTIVE CONTROL

Models of the controlled process can be used in different ways: on the one hand the knowledge about the process can be used in model based control strategies; on the other hand these models allow a prediction about the process behavior in future. Model predictive control (MPC) strategies are always nonlinear, model based and can be used for the control of linear and nonlinear processes with constraints in manipulated and controlled variables (introduction MPC short and clearly in [8]).

In every control step the MPC solves an optimizing problem: the future manipulating variables $\hat{u}$ inside the control horizon $k \rightarrow k+n_c$ shall be adapted in a form, that the process behavior $\hat{x}$ inside the prediction horizon $k \rightarrow k+n_p$ follows the given setpoints $\hat{w}$. In every control step back coupled control variables x initialize the process model for new predictions, forecasts of disturbance variables $\hat{z}$ getting an update and the optimal solution for manipulate variables u, thus a closed loop follows. To work with the fuzzy process variables it is necessary to implement a new rating system and the generalized structure has to be extended by additional components (figure 7).

The new rating system uses the calculation of the membership degree from predicted values to the fuzzy goals, which are not implicitly constant over the prediction horizon. The future setpoints can be changed inside the prediction horizon and may be found by stationary optimization. The fuzzy setpoints may be defined, preferably based on expert knowledge, which can also be integrated into a knowledge based system, so that also a non-expert can define them in interaction with a setpoint generator.

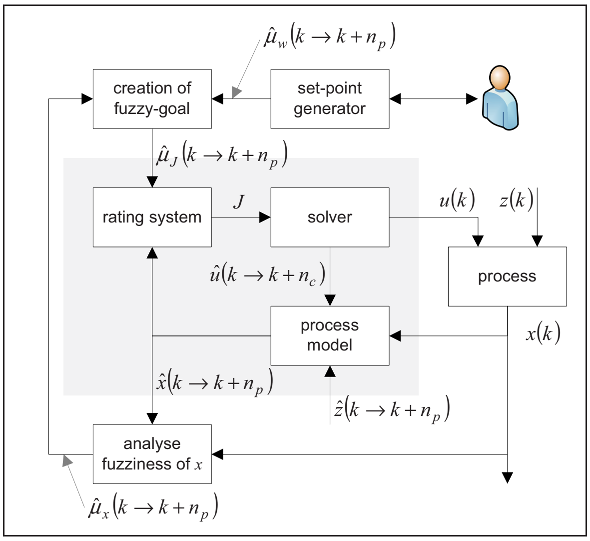

Figure 7: Generalized structure for MPC extended for considering the fuzziness in process values

As the fuzziness of actual values can change inside the prediction horizon - a general rule is, that caused by prediction errors the fuzziness is growing over the horizon. An additional tool will have to analyze the prediction errors comparing predicted with measured values and formulate the relation between predicted values and their fuzziness. By final aggregation of fuzzy setpoints and actual values a fuzzy goal can be defined for every prediction step. Computing the aggregation operation of setpoints and actual values it is advisable to use the pessimistic version, so that the prediction errors are considered strongly.

$$\hat{\mu}_J(k \to k+n_p) = \begin{bmatrix} \hat{\mu}_J(k) \\ \hat{\mu}_J(k+1) \\ \vdots \\ \hat{\mu}_J(k+n_p) \end{bmatrix} = \begin{bmatrix} G\{\mu_w(k), \mu_x(k, x_M)\} \\ G\{\mu_w(k+1), \mu_x(k+1, x_M)\} \\ \vdots \\ G\{\mu_w(k+n_p), \mu_x(k+n_p, x_M)\} \end{bmatrix} \quad (8)$$

3.1. Formulation of the objective function

In every iteration step of the optimization process a sequence of ratings between 0 and 1 occurs over the prediction horizon. For a manual optimization it is possible to make a monitoring of all pareto optimal solutions and the user selects the best one. For an automatically control the computer has to select the best solution. Hence all individual valuation will be combined to a scalar, the finally criterion scaled between 0 and 1 resulting in a new (multidimensional) fuzzy goal. There are various options to aggregate the ratings inside the prediction horizon:

- s-norm based operations: the goal is to maximize one of all individual ratings. This approach is not suitable for predictive control, because the task is not to get the best rate in the horizon at one time.
- Sum based operations: the goal is to maximize the ensemble of all individual ratings, but an individual rating alone carries no big weight. An easy way is to use the sum-criteria, but this is not scaled between 0 und 1. An alternative is the calculation of the mean of all individual ratings. This is suitable, if individual ratings with a very low rating are tolerable.
- t-norm based operations: the goal is to maximize lower individual ratings. This is suitable, if high individual ratings can be waived, because lower ratings will be compensated by higher ratings, so that the individual ratings get equalized.

If the focus of control is to prevent inappropriate situations, t-norm based operations should be applied, like depicted in [9]; more information to this topic is given in [10]. For the realization of the t-norm the minimum function should not be used, because here the view lies only on the lowest one of the individual ratings – the others are unconsidered. The easiest method is to use the algebraic product:

$$\mu_J(k) = \prod_k \hat{\mu}_J\left(k \to k+n_p, x_M(k \to k+n_p)\right) \quad (9)$$

This objective goal is one of maybe more possible single objectives, which has to aggregate to an overall goal, with the same options as above. Using weighted sum-criteria (normalized follows mean criteria) up to avoid very small ratings as follows:

$$J(k) = \frac{1}{i} \sum_i \alpha_i \cdot \mu_J^i(k) \quad (10)$$

The task of optimization is to find the manipulating variables at every step, in which J got the maximum.

3.2. Optimization operations

A crucial task in the design and operation of MPC is the optimization of the manipulating variables, in which the various strategies can be applied. The task can be characterized as a nonlinear problem (independent from the process model, fuzzy goals are already nonlinear), which does not necessarily result in a convex solution space. Thus existence of a single minimum cannot be ensured. To find the global optimum of the problem considering the process bounds a global search algorithm should be used.

For this task especially stochastically methods are of particular interest: many actuators in processes have various adjust options, some are continuous others have binary states, which can be integrated in stochastic search algorithms. In some cases only a few options for the manipulation of the process behaviour are possible. If there is enough computing time, all options can be tried and the best one selected. Latter was used in the following case study to avoid stochastic effects there.

4. CASE STUDY

In order to illustrate feasibility and validity of the proposed method a case study has been done. A typical application for the described method is the automation of an air conditioning process. The setpoints of climate goals are not defined by precise real numbers; they are rather tainted with fuzziness. The mathematical definition of the stationary setpoints is already a compromise found by a multi criterion optimization problem with the weighted controversial issues *operation cost* and *demand of occupants (comfort and health)*. Just in the air conditioning of historical buildings and rooms, in which cultural heritage is warehoused (museums, libraries, depots, archives, etc.) the special demands of preventive conservation are added to avoid climate damages.

4.1. Task description

In the case study the relative air humidity of a room has to be controlled, such that the actual values correspond to the fuzzy setpoint in figure 8 (above, dark line). The only actuators are a humidifier and a dehumidifier, every system can switch between the states *off*, *half,* and *full operating*. In comparison to other task of control engineering the air conditioning is a slow process with larger time delays; so time consuming calculations are possible.

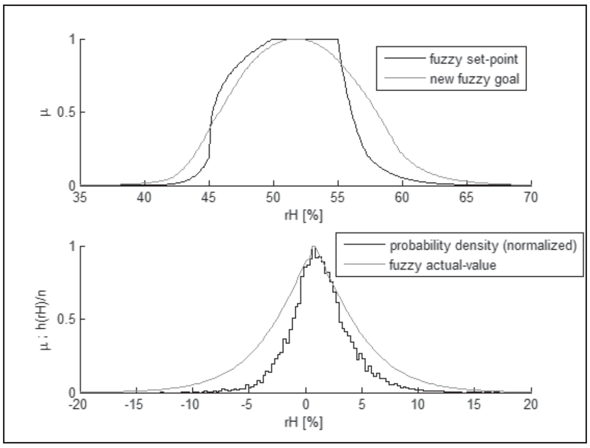

Figure 8: Above: setpoint under fuzziness and new fuzzy goal by considering the fuzziness in actual values; below: normalized probability density for prediction error and approximation by a membership function (both graphs for the sixth forecast step, 6h)

4.2. Process model and control strategy

A mathematical model of the indoor climate can be defined by equations of energy and mass balance, for more details look at the references [1], [11] and [12]. The model used is based on a one hour sampling time. It is considerably simplified in contrast to state of the art detailed hygrothermical models. Following parameter identification a validation with simulations based on exact models (WUFI, description in [13]) has been carried out.

The MPC strategy uses an equal length from 12 steps accordant 12 hours for prediction and control horizon. The task is to optimize the actuator signals; therefore 4 optimization variables with 5 states (*full* and *half dehumidification*, *off*, *full* and *half humidification* -1, -0.5, 0, 0.5, 1) are to calculate:

- the first variable for the first hour
- the second variable for the second hour
- the third variable for hours three till seven
- the fourth variable for hours eight till twelve

4.3. Prediction errors and fuzzy actual values

The same model is used for the simulation of the controlled process and for internal predictions. To analyze the effect of prediction errors, an error signal has been generated and added to the ideal prediction. The signal has been calculated at an exponential function (for outdoor temperature an absolute humidity), where the time constants and final values were generated as random numbers inside a typical range. In each prediction step a distribution for the prediction error is ascertainable (may be based on logged data).

After normalizing the resulting probability destiny function, an approximation to the function with a membership function based on standard equations (here based on the difference of two sigmoid functions) may be defined in a way that the possibility degree is higher than the normalized probability degree (see section 1). The fuzzy setpoint is constant inside the prediction horizon. So the new fuzzy goals may be calculated for each prediction step.

An example for the sixth prediction step is shown at figure 8. Usually the exactness of the prediction decrease over the prediction horizon, thus the fuzziness of predicted actual values increase (figure 9 above). For each step a new fuzzy goal like equation (8) can now be defined and a criterion for each prediction can be calculated.

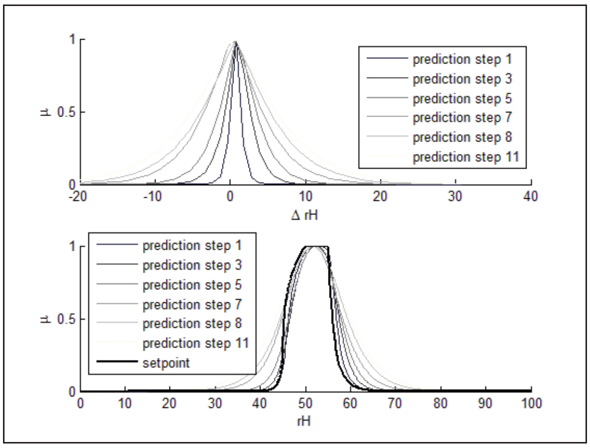

Figure 9: Fuzziness in actual values (above) and fuzzy goals (below) over the prediction horizon

4.4. Simulation results over one year

The first simulation case represents the best case scenario: the prediction is ideal without errors – in contrast to the worst case scenario, in which the predictions are inexact caused by the additional error signal. The conventional method to consider the prediction error is to use the expected values of the predicted values instead of the values itself. The effect is illustrated in the cumulative performance error over one year (figure 10).

Comparing the best with the worst case it becomes obvious, that an optimization of the expected values reduces the control errors. In the next simulation case the calculated fuzzy goals are used, which were developed like described in sections before. Here is an additional benefit to notice, so that the consideration of the fuzziness in actual values is not unappreciative.

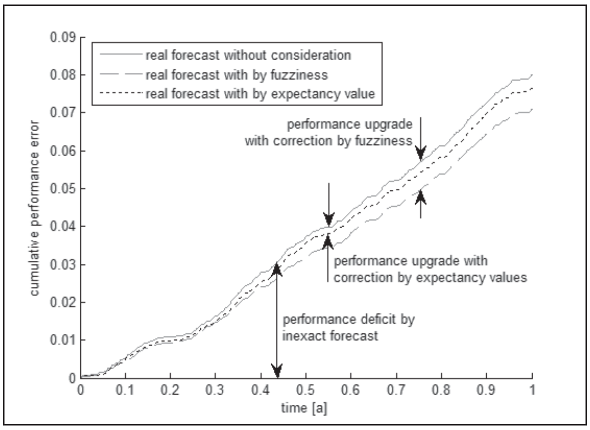

Figure 10: Cumulative performance error in simulation scenario (cumulative difference between run at ideal forecast and various corrections)

5. FOLLOWING WORKS

In future research studies the here presented methods will be extended in processes with more options for the manipulation of the process and to MIMO cases. The new presented approach will also be applied in practical case studies using special air condition tasks, especially for control and stabilization of the relative humidity in libraries, museums and historical buildings for the purpose of preventive conservation.

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